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EXTRACTION OF 9,163 REAL LV NETWORK MODELS FROM DNO GIS DATABASE TO ASSESS OVERVOLTAGE FROM PV AND CONSEQUENT MITIGATION MEASURES

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ABSTRACT

The scale of the overvoltage problems that will be seen across a Distribution Network Operator's low voltage network is quantified for increasing levels of solar photovoltaic integration. This is completed on 9,163 real low voltage network models which have been extracted using a bespoke method from a Geographical Information System. Two configurations of distributed energy storage are investigated; home storage randomly taken up by customers; and storage directed by the Distribution Network Operator to areas where it will give the greatest effect on overvoltage problems. It is found that a planned approach is more effective in mitigating overvoltage than if consumers adopt storage in an ad-hoc manner, although the later can bring advantages.

INTRODUCTION

Rooftop solar photovoltaics (PV) are the most widely connected form of distributed generation in European low voltage (LV) power networks in terms of the number of systems installed (e.g. [1]). As well as positive impacts, PV can have negative effects on distribution networks. These are widely studied on small numbers of LV networks (e.g. [2]–[4]). Such issues can be problematic and costly for Distribution Network Operators (DNOs).

DNOs do not always maintain models of their LV networks. Therefore, to investigate a particular LV network, a DNO might manually build a network model by looking at their Geographical Information System (GIS). However, this slow process prohibits production of the large number of network models needed to allow assessment of the cost implications from PV across all of a DNOs LV distribution networks. Alternatively, a large number of LV models can automatically be extracted from a DNO's GIS database, such as in [5]. A custom made procedure for doing so is presented here. By using models extracted using this method from an entire DNO's operating area, real technical and financial implications of PV on a large number of LV networks are presented.

To mitigate any problems due to PV, new methods are needed to reduce costs. Therefore an assessment is also performed into how to install energy storage in LV networks to mitigate problems associated with PV. Such results have relevance for both DNOs and policy makers.

THEORY

As shown in Figure 1, an LV network has a secondary (MV/LV) transformer with a number of LV fuses/circuit breakers. From these fuses, a number of LV feeder cables run above or below ground. The feeder cable can split into sub-feeders and is connected to homes and businesses through service cables as shown.

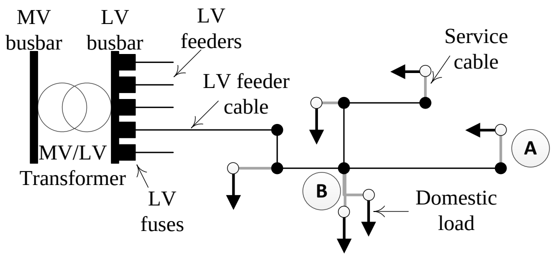

Figure 1: Overview of a typical LV network

GIS maps the configuration and location of cables/other components in a DNOs distribution network. Typical parts of GIS are shown in Figure 2 and Figure 3 in which the various components previously described can be seen. It is noted that service cables usually enter a home or business perpendicular to the orientation of the roof. This is useful for estimating where PV might be installed in residential LV networks. Since the GIS system is held electronically, it is possible to computationally extract LV network models from it.

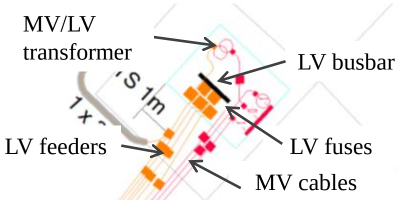

Figure 2: Components around a MV/LV transformer in GIS

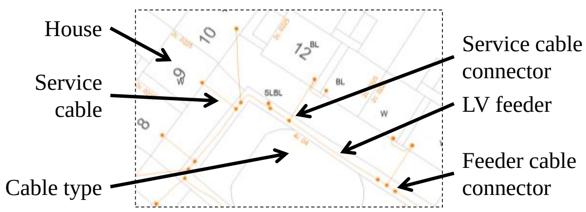

Figure 3: Typical section of LV network in GIS

EXTRACTING LV MODELS FROM GIS

The basic concepts of a procedure to extract models from GIS are now presented. A pre-analysis is first completed:

1. The GIS map is converted to shapefiles to be analysed in Matlab.
2. LV transformers are identified as those having LV fuses in their vicinity. The number of feeders with each transformer is equal to the number of LV fuses.
3. Feeder cables are joined by connectors. A proximity analysis associates cables with each connector.
4. The cable type is found by finding the cable type label closest to each cable.
5. The number of loads connected to each service cable is determined by the number of cable ends, e.g. cable **A** in Figure 1 has one load, cable **B** has two loads.
6. The orientation of each service cable relative to North-South is determined.

Then, the method outlined in Figure 4 is completed using Matlab. The key concepts are as follows:

- Each transformer, t is assessed individually.
- To lower the computational effort, LV network components within 10 km of t are extracted from the raw GIS data before analysis of each transformer, t.
- The cables in each feeder, f are found sequentially using cables associated with connectors in f.
- Loads are connected to the feeder by service cables. Each service cable is associated with a feeder cable.
- Feasible locations for PV are identified by the orientation of the service cable to North-South since cables usually enter houses perpendicular to the roof.

Validation of Method

The method is applied to the GIS of a UK DNO (Electricity North West (ENWL)). It identifies and generates LV network models associated with 28,642 secondary transformers. Of interest for study of PV are residential urban networks where the most PV is likely to be installed. These also have the most intricate cable layouts and the highest number of customers. Therefore, models of these networks are harder and more time consuming to build.

To identify these, only networks which meet a number feasibility criteria are used (Table 1). 9,163 networks are found to do so containing 43,816 LV feeders and 1,292,960 homes with south facing roofs. Of the unselected networks, 74% are farms, commercial or industrial customers. Small village networks are also rejected. The networks have been compared to 11 manually created models with errors up to ±10% in the number of loads/PV and errors up to ±4% in the feeder cable length.

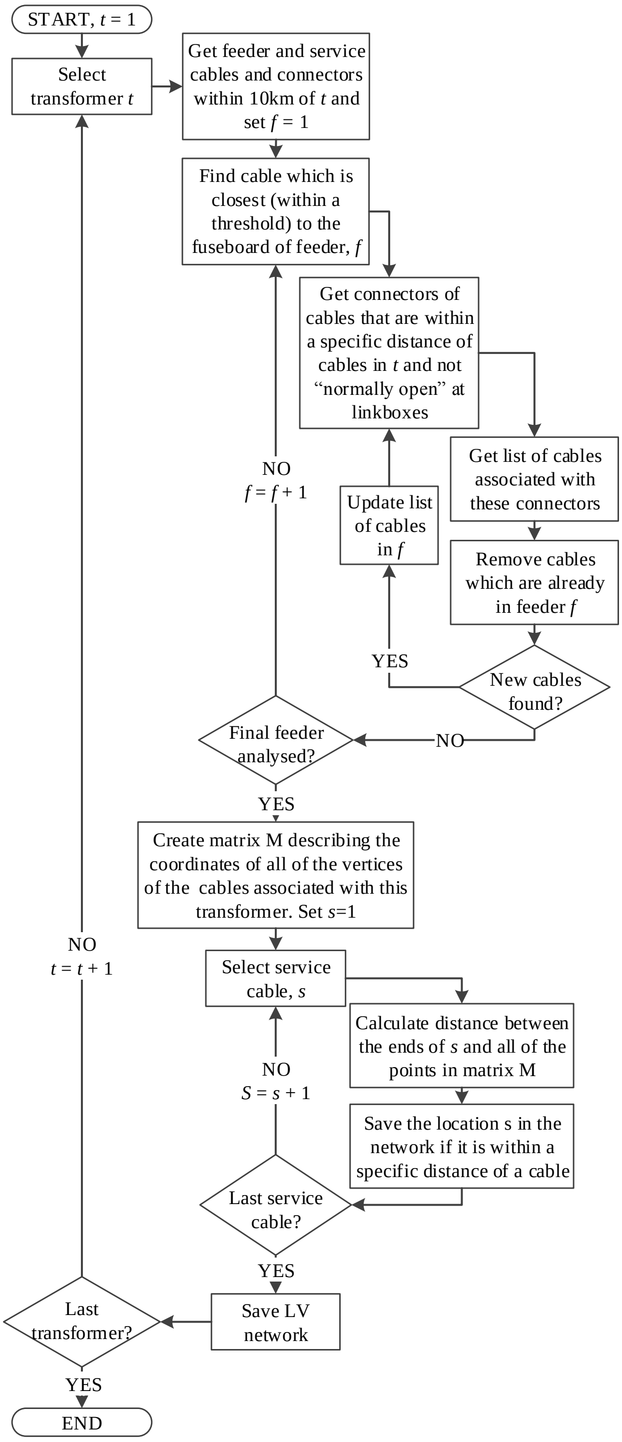

Figure 4: Method for extracting LV networks from GIS

Table 1: Feasibility criteria

Parameter	Min	Max
Loads on a feeder	-	200 loads
Total number of loads	50	1,200
Length of longest feeder	10m	800m
Total feeder cable length	50m	12,000m
Number of feeders	1	25
Voltage drop when loads at 1 kW	-	0.12 p.u.

ASSESSING LV PV AND ENERGY STORAGE

A method for assessing the impact of PV on the GIS derived LV networks is now described. The method focuses on the particular issue of overvoltage. In LV networks, steady state voltages cannot be larger than 1.1 p.u. or less than 0.94 p.u. [6]. Each network has variation in the voltage at the secondary transformer between a maximum, $V_{T,max}$ and minimum, $V_{T,min}$. With no PV or other forms of distributed generation, LV network voltages decrease along the feeder cables. The largest voltage drop, ΔV_{LV}^{-} occurs when loads are at maximum value and networks are designed so that

$$1.1 - 0.94 \geq \left(V_{T,max} - V_{T,min}\right) - \Delta V_{LV}^{-}. \quad (1)$$

From a DNO's perspective, PV is installed on a random set of homes with south facing roofs. Residences with south facing roofs can be identified in the GIS since the orientation of the service cable (a proxy for roof orientation) is known. With PV, there is a chance that there will also be and LV voltage rise, ΔV_{LV}^{+} which might cause the upper voltage limit to be exceeded (overvoltage). If there is overvoltage, the following equality is not held

$$0.16 \geq \left(V_{T,max} - V_{T,min}\right) - \Delta V_{LV}^{-} - \Delta V_{LV}^{+}. \quad (2)$$

In a load flow, this is determined by setting loads to their lowest value and setting generation to export at rated power. Since the location of PV is uncertain, a stochastic approach (e.g. [7], [8]) needs to be used to locate it.

LV energy storage

In the event of overvoltage, a DNO could reconductor a feeder to decrease its impedance. An alternative is energy storage. This reduces the voltage rise from PV if it is controlled to reduce reverse power flow. In LV networks there are three possible locations for storage (Figure 5):

a) Storage at the transformer, managing MV voltages.
b) Storage purchased for homes in an arbitrary way to improve PV self-consumption.
c) Storage placed in the network at locations determined by the DNO.

Storage at the secondary transformer can only have a limited effect on LV voltage since it cannot directly influence LV voltage rise, ΔV_{LV}^{+}. Storage in homes and on the feeder can influence both the LV and MV voltages.

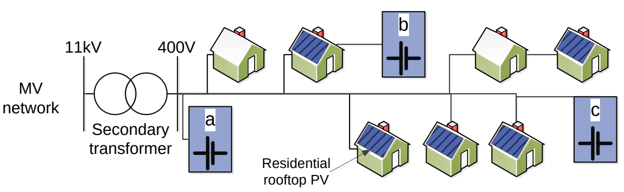

Figure 5: Possible locations for storage in an LV network

Storage randomly fitted by homeowners lowers voltage and has financial benefit to customers in improving PV self-consumption. However it might not necessarily be placed at the best locations to influence voltage. Storage sited and owned by the DNO can fix voltage problems [9] and can accrue other benefits such as those listed in [10]. However, the financial benefits to a DNO relative to reconductoring are uncertain, particularly because the differing properties of a large number of LV networks need to be considered.

Integrated LV Energy Storage Assessment

The integrated method summarised by Figure 6 allows assessment/comparison of storage types b and c in relation to voltage control and considers stochastically located PV. For each network, n, the voltage drop, ΔV_{LV}^{-}, is first calculated by setting all loads to their after diversity maximum demand (ADMD) value with no PV or storage in a model. Then PV is randomly added on south facing roofs in each LV network, n with probability p_n and loads are set to their minimum value. This establishes the conditions where voltage rise is highest.

If the DNO is to locate storage at optimal locations then a genetic algorithm is used [11]. This will always prevent overvoltage and such a method is needed to find the optimal number and location of storage amongst many possibilities. Alternatively, storage is located in homes with PV with probability q_n. By setting $q_n = 0$, and studying a range of p_n values, the total range of voltages in a network and the greatest allowable p_n can be determined. The tool is implemented in Matlab using OpenDSS to perform load flows.

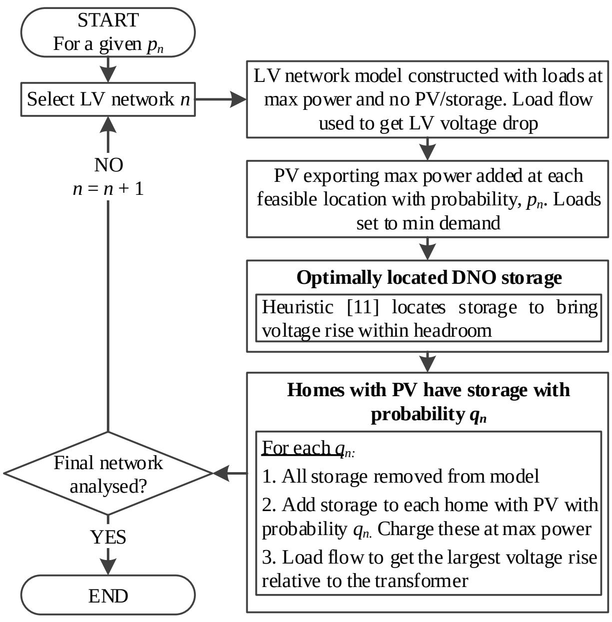

Figure 6: Summary of the method for assessing randomly located PV with randomly or optimally located storage

RESULTS

To determine how many LV feeders are expected to have overvoltage, the tool in Figure 6 is applied to the networks extracted using the method in Figure 4. To determine voltage drop, an ADMD of 1.4 kW is applied. If $\Delta V_{LV}^{-}$is more than 0.12 p.u., then a 1 kW ADMD is used. The highest voltage rise is when PV exports rated power and demand is lowest. 3.6 kW PV is used as this is average PV rating within the distribution network under study. The minimum average demand is 0.142 kW as found in measured values [12]. The voltage variation at the secondary transformer, $(V_{T,max} - V_{T,min})$ is 0.04 p.u. using the same measured values. Three cases for future LV storage from a DNO's viewpoint are considered. The same p_n and q_n are used on each network:

1. A negligible market for LV energy storage exists and the DNO reconductors LV feeders with overvoltage.
2. Storage is randomly installed by 5%, 25% or 50% of PV owners. This has the same rating as the PV. The DNO reconductors feeders with overvoltage.
3. A negligible amount of homes install storage. Where cheaper than reconductoring, the DNO locates three-phase 25 kW storage in LV feeders on the street at locations found using the genetic algorithm [11].

Figure 7 shows the number of feeders which experience overvoltage under the different storage scenarios and with different amounts of PV, p_n. The dark blue line is the number of LV feeders which experience overvoltage with no storage ($q_n = 0$). Of the 43,816 feeders, with PV at 30% of homes with a South facing roof, fewer than 1,600 have overvoltage. If storage is located with a random selection of single-phase PV installations, then a decreasing number of the LV feeders experience overvoltage (green, red and light blue lines). If the DNO locates storage using the genetic algorithm, then no feeders have overvoltage.

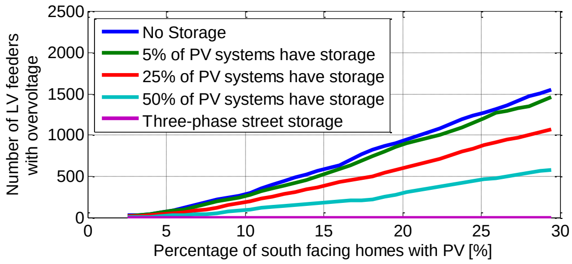

Figure 7: Number of LV feeders which have overvoltage with different amounts of PV and storage

The amount of storage needed in these scenarios is shown in Figure 8. To prevent all overvoltage, the DNO needs to install storage equivalent to between 5% and 25% of homes purchasing storage. For storage to be a viable alternative for DNOs, it needs to cost less than reconductoring. To assess this, an illustrative cost comparison is performed. Feeders are reconductored at £80/m (as in [11]) and the storage cost is $2,018/kW (£1,286/kW), with a 4 hour discharge and 1 cycle per day for 250 days a year [13].

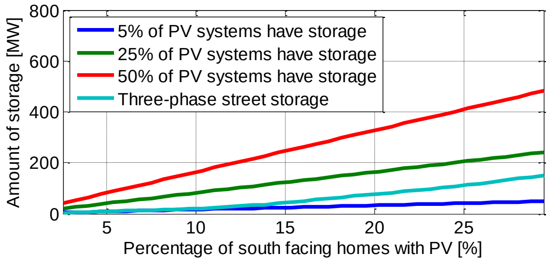

Figure 8: Amount of storage under different scenarios

The cost to the DNO of the storage scenarios is shown in Figure 9. It can be seen that the cost of reconductoring the LV networks is up to £120 million without storage. If customers purchase storage, then this will decrease the reconductoring cost. However, the DNO needs 50% of customers to install storage before the reduced reconductoring cost is similar to DNO owned storage.

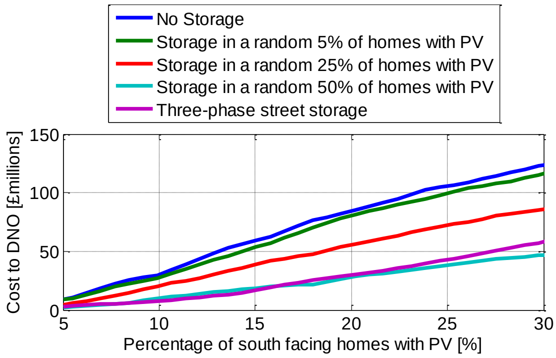

Figure 9: Cost to DNO of different storage scenarios.

Figure 10 shows the cost of reconductoring and storage per kW of PV installed. It can be seen that a policy which supports the ad-hoc adoption of storage in homes adds much more overall cost to the power system then a policy which encourages DNOs to install storage within their LV feeders. Under the cost model presented, this shows

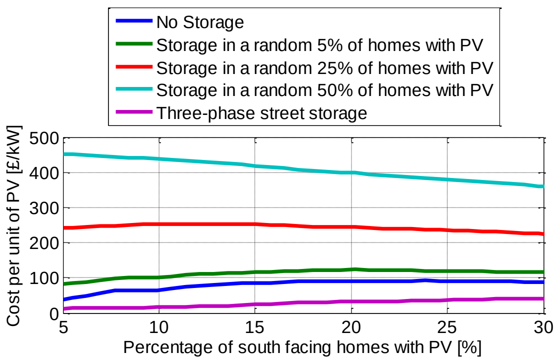

Figure 10: Cost of storage and reconductoring per kW of PV for each energy storage scenario

that DNOs should look at using storage over reconductoring. Storage installed in homes is found to be the least cost effective way of managing overvoltage when the costs not met by the DNO are considered.

DISCUSSION

Large numbers of LV network models are needed for DNOs to fully understand how low carbon technologies will impact LV distribution. A number of standard models exist for this, however these are limited in number and do not represent all real LV networks. This work shows that it is practically feasible to extract large numbers of LV networks from GIS and to then use them with simple tools to acquire important policy, financial and technical results. This is important because, as shown by this work, thousands of LV feeders might soon require reinforcement due to PV. A full description of the method is available in [14]. Results for this paper were obtained within a week of desktop computational processing.

The cost to a DNO for LV network overvoltage is found to be quite low (<£120million) under large PV integration and the extreme network loading applied (the total asset value is of the order of £billions). Such cost estimates are important to determine if and how further PV integration should be supported by regulators and Governments to achieve a low carbon power system. The models could also have been used to determine costs for increased peak demands breaching thermal limits in LV networks. This can influence policy and business decisions about electric vehicle charging, electric heating, and whether to support installation of demand side response or time of use management within LV networks.

Considering the results, a DNO would benefit from any policy which encourages customers randomly purchase storage because it reduces reconductoring costs (Figure 9). However, it is found that this is the least cost effective way of preventing LV overvoltage when the storage cost is included (Figure 10). Therefore, this work concludes that DNOs should consider storage as an alternative to reconductoring. Detailed study of problematic LV networks and ongoing LV storage trials will help determine the financial feasibility this. Further, it is emphasised that the proposition for storage will be different on different LV networks.

CONCLUSION

Assessing large numbers of LV feeders is both feasible and valuable. This been demonstrated by assessing PV and storage. DNOs and policy makers should maintain large numbers of real and accurate LV models to measure the policy and financial implications of different low-carbon pathways in the changing power system.

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